Stochastic-based Deterioration Modeling of Elevators in Healthcare Facilities

Reem Ahmed
Department of Building, Civil, and Environmental Engineering
Concordia Univeristy
Montreal QC, Canada
reem.ahmed@mail.concordia.ca

Ahmed Assad
Department of Building, Civil, and Environmental Engineering
Concordia Univeristy
Montreal QC, Canada
ahmed.assad@mail.concordia.ca

Eslam Mohammed Abdelkader
Department of Building, Civil, and Environmental Engineering
Concordia Univeristy
Montreal QC, Canada
eslam_ahmed1990@hotmail.com

Tarek Zayed
Department of Building and Real Estate (BRE)
The Hong Kong Polytechnic University
Kowloon, Hong Kong, China
tarek.zayed@polyu.edu.hk

Fuzhan Nasiri
Department of Building, Civil, and Environmental Engineering
Concordia Univeristy
Montreal QC, Canada
fuzhan.nasiri@concordia.ca

Abstract—Deterioration and aging associated with building assets are becoming major concerns in most countries as their building portfolios continue to increase and expand. Healthcare facilities are a special case of building assets that inherit a significant criticality and complexity within its operation and maintenance regimes which makes monitoring the assets' condition and forecasting their life expectancy two of the most essential functions in a healthcare environment. In this paper, a stochastic deterioration prediction approach was developed to model and estimate the degradation of elevators systems within hospital building environments due to their importance to the continuity of the hospital mission and services. Different probability distributions were fitted using historical condition data and the performance of different distributions was then compared utilizing the Anderson-Darling test. Parameters of the best distribution were thus found using maximum likelihood estimate. The developed model is expected to aid decision makers in improving the planning process for their maintenance and rehabilitation programs and to efficiently conduct proactive maintenance activities in a timely manner which helps ensure the sustainability of hospital operation.

Keywords—deterioration prediction; Weibull probability distribution; Anderson-Darling test; maximum likelihood estimate; healthcare facilities

I. INTRODUCTION

Evaluating the condition and performance of hospital building assets is considered a vital step in the process of predicting the expected deterioration in building components occurring due to aging, obsolescence and exposure to the surrounding environment [2]. Deteriorating buildings and facilities often require significant upgrades to improve their economic, operational and environmental performance [1]. Given the complex and dynamic nature associated with healthcare facilities, a systematic maintenance management framework is considered essential for efficiently operating and upkeeping the hospital building assets. And due to the recurring issue of scarcity of funds allocated to hospital operation and rehabilitation, a maintenance budget planning model is deemed necessary. One of the core functions linked with budgeting the maintenance and renovation activities is the prediction of the life expectancy of building assets [5]. However, being dependent on the deterioration process occurring in the building assets as a result of the in-use conditions, life expectancy prediction and estimation is not an exact science and is even referred to by some researchers as an "uncertain process" [10]. In addition to that, [16] have rated the forecasting and estimation of the deterioration pattern estimation as the most complex task to perform within the facility management of hospitals and healthcare facilities. This conclusion was linked with the variability of users and stakeholders in hospital environments as well as their different objectives, needs and satisfaction measures.

II. LITERATURE REVIEW

In general, asset components' deterioration is predicted by utilizing either deterministic, artificial intelligence-based or probabilistic/stochastic approaches [15].

For the deterministic approach, the use of codes and standards is considered crucial for the identification of the Reference Service Life (RSL) that guides experts involved in the forecasting process to give a robust and sound estimation of the Expected Service Life (ESL) of the assets [11]. This can be illustrated as per the case of hospitals in the National Health Service (NHS) of the United Kingdom; where the current assessment process of the overall remaining service life of the hospitals is done by deriving the arithmetic mean of all the remaining service life values for all hospital building elements obtained through expert judgement [13].

Straight-line extrapolation, regression-based methods and curve fitting are three of the mostly used deterministic procedures of predicting the deterioration of building assets [21]. Due to the relative simplicity associated with deterministic models, several researches have explored its applicability on estimating the service lives of buildings and healthcare facilities. For example, [16] developed a maintenance expenditure planning framework for hospital buildings based on several criteria including the facility age. A conclusion was then drawn as part of this study that concrete structural elements in hospital facilities experience a linear deterioration for the first 15 years in their service lives and continue deterioration on an exponential basis thereafter. [23] have also utilized a hybrid-deterministic deterioration prediction models to estimate the service live of building elements, specifically façade systems, that are undergoing a failure state. Furthermore, [22] created a reliability-centered maintenance management model based on the current performance of the hospital assets, that uses expert surveys and questionnaires to determine the duration between the potential point of failure and functional failure point (P – F) for hospital building components based on their experience-driven preferences. However, as it can noted from the researches involving deterministic approaches to predicting the deterioration, a high level of uncertainty is evident since the output is a single value representing the service life of the building element [10]. Also, another limitation of using deterministic approaches is its dependence on age and time as the sole indicator for building degradation [20].

The second type of deterioration prediction methodologies is artificial intelligence-based models. This type of models is highly data-intensive requiring timely detailed condition monitoring and reporting to design, train and validate the models. They include artificial neural networks, fuzzy set theory, and case-based reasoning. However, due to the scarce and limited nature of data collection and availability within the healthcare environment, the applicability of such models remains unexplored [7].

The last type of deterioration prediction models is the probabilistic/stochastic models. Stochastic prediction approaches are categorized into two main categories: 1) Time-based models (i.e. Weibull Probability Distribution models) that estimate the probability distribution of the duration spent for the component to change from one state to the other, and 2) State-based models (i.e. Markov models) that predict the probability of building components experiencing a deterioration or a transformation in its current condition within a given time duration [5]. Extensive research has been conducted in this area with regards to building deterioration prediction, as probabilistic/stochastic frameworks possess a proven applicability to complex environments like buildings and healthcare facilities [8]. Also, stochastic models are superior to other prediction models like deterministic ones as they have an ability to account for uncertainties, subjectivity and errors in assessments and initial conditions as well as applied stresses on building components [17]. Advantages of using stochastic Markov chains to predict building deterioration include their inherent ability to depend only on the current or previous observed condition state in order to predict a future state given their memoryless nature [18]. This encouraged researchers to apply Markov chains to forecast future conditions of a variety of asset types including linear networks like wastewater networks, stormwater pipes, pavements and bridge elements, as well as complex hierarchical structures like building assets and facility components [6]. To begin with, [9] developed a time-based stochastic self-correcting deterioration prediction model that uses Weibull probability distribution to estimate the condition of building components over time. The model utilizes current and past condition inspections to provide an accurate projection of the components' service life. On the other hand, state-based deterioration models have been more popular for application in building and hospital environments. [18] studied the generalization of infrastructure transition probabilities assuming constant inspection durations corresponding to the cycle time. Moreover, a study by [8] developed an asset deterioration prediction model for buildings owned by the U.S. Department of Defense (DoD) that utilizes a semi-Markov model to estimate the expected condition of building assets over the transition intervals accounting for the previous condition state observed for each component as well as the time elapsed since the last inspection. Finally, a study was conducted by [6] proposing a Markov model developed as per extensive analysis of the factors available in the International Standards Organization's (ISO) method with the goal of determining the effect of a limited set of variables on the deterioration of building components over a fixed duration. Despite its relative complexity compared with the deterministic approach, the stochastic and probability-based deterioration prediction approach provides a sounder estimation of the depreciation inside the hospital building which results in a more efficient budget planning and allocation for maintenance and rehabilitation activities [24].

As it can be noted from the literature review previously presented, the number of studies conducted on predicting the deterioration expected within hospital facilities components is significantly limited compared to the studies conducted on buildings of a general-use ignoring the complexity and importance of healthcare facilities and their underlying elements that need to efficiently work with maximum performance around the clock, and any downtime expected as part of a component's failure should be minimized by proper planning and monitoring of the overall condition of building components. Another noteworthy observation would be the inefficiency of the methods utilized in previous studies to model the hospital building components, as they mainly relied on deterministic methodologies that are not considered an appropriate representation of the actual reliability distribution of the hospital components. Accordingly, this paper experiments multiple algorithms and probability distributions in order to propose a reliable stochastic-based deterioration prediction model for hospital building elements. The hospital components selected for the purpose of this application are hospital building elevators due to their significance and criticality pertaining to the overall hospital mission.

III. Model Development

The first step in the developed methodology is retrieving the relevant datasets from Canadian hospitals representing the resulting reports and commentaries from the expert-based visual inspection process conducted inside the hospital facility to gauge the performance of building assets and ensure continuity of hospital operation. The datasets were collected from 25 hospital buildings in the province of Alberta, and the datasets included resulting datapoints obtained upon visual examination of hospital building assets by professional engineers. The relevant parameters are extracted from the datasets to model the deterioration of the different components in healthcare facilities. The extracted data include the name of the system, type of the system inspected, its installation year, the year when the inspection was conducted, and the observed physical condition. The installation year is important to calculate the age of the system at a specific inspection year. The data consists of different systems such as slab on grade, structural, exterior walls, elevators and conveying systems, hot water distribution system, oxygen gas pipes, and others. The scope of this study is focused on modelling the deterioration of the elevators due to the fact that within healthcare facilities environments, elevators represent an integral part of the conveying system that carries patients, visitors, medical and supporting staff, medical equipment and supplies, as well as managerial staff. The condition data of the inspection reports are used to model the deterioration behavior of elevators based on reliability and survivability theory. In this application, various probability distributions are investigated to fit the available condition data. Eight different distribution are fitted in this study to select the best performing one in estimating the determination of the elevators. These distributions are normal distribution, Weibull distribution, exponential distribution, extreme value distribution, and lognormal distribution. Maximum likelihood estimates are used to determine the parameters of each distribution. Moreover, Anderson-Darling test is used to compare and select the distribution with the best calculated performance. Below is a brief description of each distribution along with an explanation of the statics of the Anderson-Darling test.

Normal distribution is a continuous probability distribution that is often used in the natural and social sciences application to model real-valued random variables. It is commonly used when not enough information is known about the nature or the outcome of the process. The general form of the probability density function of normal distribution is given by [3] in the equation below.

$$f(x)= \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \tag{1}$$

Where μ is the mean of the distribution and σ is the standard deviation. In 1939, Waloddi Weibull developed a failure distribution function that is presented by a bathtub-like curve like the one shown in Fig. 1 to describe the deterioration phenomenon. Since then, his formulation has been accepted as the most popular model to asses and predict failures and malfunctions across several fields [12]. The probability density function for a 3-parameter Weibull distribution is given by Equation 2 [12].

$$f(x,\beta,\eta,\gamma)=\frac{\beta}{\eta}\left(\frac{x-\gamma}{\eta}\right)^{\beta-1} e^{-\left(\frac{x-\gamma}{\eta}\right)^{\beta}} \tag{2}$$

Where $x \geq 0$, $\beta > 0$, $\eta > 0$, $-\infty \leq \gamma \leq \infty$, β is the shape parameter, η is the scale parameter, and γ is the location parameter.

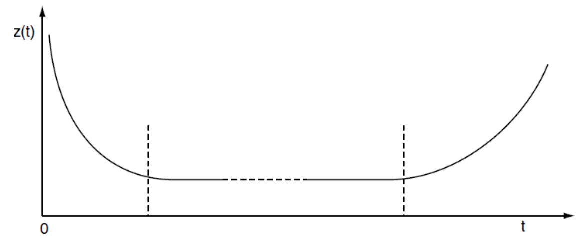

Fig. 1. Bathtub Failure Rate Function

Moreover, the exponential distribution is one of the most widely used continuous distributions as well. It is often used to model the time elapsed between events. In this case, the random variable shall always take positive values. The probability density function of exponential distribution is given in Equation 3 [19].

$$f(x)=\lambda e^{-\lambda x} \tag{3}$$

Where λ is the arrival rate.

On the other hand, extreme value distribution is a limiting model for the maximum and minimum values present within a data set. A limiting distribution models how large (or small) the data can get. The general form of the density function of extreme value distribution is given in Equation 4 [14].

$$f(x)=\frac{1}{\beta} e^{\frac{x-\mu}{\beta}} e^{-e^{\frac{x-\mu}{\beta}}} \tag{4}$$

Furthermore, lognormal distribution is a continuous probability distribution of a random variable whose logarithm is normally distributed. This variable can only take positive values. Lognormal is widely used in engineering sciences and economics fields. The general density function of lognormal distribution is given in Equation 5 [4].

$$f(x)=\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\ln x-\mu}{\sigma}\right)^2} \tag{5}$$

Where μ is the mean of the distribution and σ is the standard deviation.

Box-Cox distribution is another probability distribution that was studied in this paper. Box-Cox distribution is the distribution of a random variable for which the Box–Cox transformation follows a truncated normal distribution. The probability density function for this continuous distribution is given by Equation 6 [25]

$$f(x)=\frac{1}{(1-I(g<0)-\text{sgn}(f)\phi(0,m,\sqrt{s}))\sigma\sqrt{2\pi s^2}}\, e^{-\frac{1}{2s^2}\left(\frac{xf}{f}-m\right)^2} \tag{6}$$

where m is the location parameter, s is the dispersion, f is the family parameter, I is the indicator function, Φ is the cumulative distribution function of the standard normal distribution, and sgn is the sign function.

Another investigated distribution is Gamma distribution. Gamma is a continuous distribution function with two parameters. Probability density function of Gamma distribution is given by Equation [7] [26]

$$f(x)=\frac{\lambda^{\alpha}x^{\alpha-1}e^{-\lambda x}}{\Gamma(\alpha)} \tag{7}$$

Where x>0, λ the scale parameters, α is the shape parameter , and Γ is the gamma function.

Finally, Johnson's distribution was also examined. Johnson's distribution has a probability distributions function of four parameters. It was first proposed by Johnson in 1949 as transformation of the normal distribution, Equation 8 [27]

$$f(x)=\frac{\eta}{\sqrt{2\pi}\sqrt{(x-\varepsilon)^2+\lambda^2}}\, e^{-\frac{1}{2}\left(\gamma+\eta\,\sinh^{-1}\left(\frac{x-\varepsilon}{\lambda}\right)\right)^2} \tag{8}$$

Where ε is the location parameter, λ is the scale parameter, γ and η are the shape parameters.

The quality of fit of each of the proposed models is tested using the Anderson-Darling statistic test. The Anderson-Darling statistic is a measurement of how well the data follow a certain distribution. It is generally used to compare the fit of several distributions to determine which one is the best. This reliability testing and analysis procedure commonly incorporates three main measuring parameters:

- Anderson-Darling statistic (AD): A Lower AD values indicates a better fit. Nevertheless, to compare between the suitability of different distributions to fit the data, p-value should be assessed.
- P-value: A higher p-value indicates a better fit. A low p-value (e.g., < 0.05) indicates that the data do not follow that distribution and other distribution shall be tested. It should be noted that the p-value could not be calculated for 3-parametrs distributions.
- LRT P: A lower value indicates significantly improvement realized by adding the third parameter over the 2-Parameter version.

IV. Results and Discussion

As previously mentioned, eight different distribution are fitted within the proposed model to select the most representative modeling pattern of simulating the deterioration expected in the elevator systems in healthcare facilities. Table 1 shows a comparison of the results of the Anderson-Darling test for the five distributions utilized.

Table 1: Comparison of the Anderson-Darling statistic test results

Distribution Type	P-Value	AD Statistic
Normal	0.1491	0.5455
Weibull	0.1650	0.4797
Exponential	0.0065	2.0534
Extreme Value	0.0110	0.5783
Lognormal	0.1389	0.5052
Box-Cox Transformation	0.1298	0.6258
Gamma	0.1537	0.5104
Johnson Transformation	0.1395	0.5898

It can be observed from Table 1 that the Weibull distribution fits the condition data the most. This is evidenced by the highest P-value and lowest value of AD statistic. It is also observed that all the distribution could fit the deterioration of the elevators with acceptable range except for the exponential and extreme value distributions. The P-value for these distributions was less than 0.05 which suggests the rejection of the null hypothesis (the distribution cannot fit the observed data).

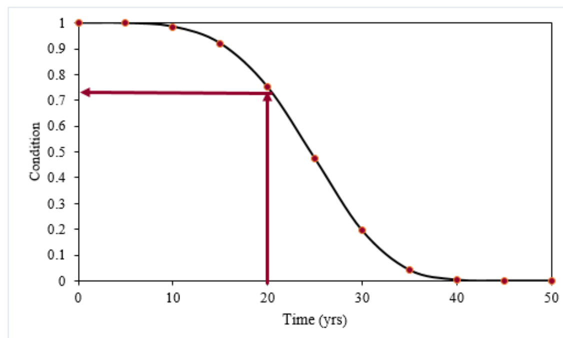

Fig. 2. Elevator Deterioration Function

Using the maximum likelihood estimate, the parameters of the 2-parameters Weibull distribution was found. The values of the shape parameters and scale parameter are 4.30 and 27.75 respectively. Once the Weibull distribution parameters are computed for a healthcare-based elevator system having similar covariates, the reliability function of this system can be calculated by integrating the failure probability density function. The reliability function and the failure rate associated with a 3-parameter Weibull distribution are given by Equations 9 [12].

$$R(x)=e^{-\left(\frac{x}{\eta}\right)^{\beta}} \tag{9}$$

Where x is the age of the elevator, β is the shape parameter and η is the scale parameter. A Weibull distribution with a shape factor (β) less than one corresponds to a decreasing failure rate over time, corresponding to an improving reliability. This phase is known as infant mortality phase or early-life failures. On the other hand, a Weibull distribution with (β) more than one corresponds to an increasing failure rate over time, corresponding to a deteriorating reliability. This phase is known as wear out phase or end-life failures. In exceptional cases when the Weibull distribution has a shape parameter (β) that is exactly one, this corresponds to a constant failure rate. In this study, the found shape parameter is more than 1 which indicates a wearing out phase. The scale parameter η determines the spread of the Weibull distribution. A higher value of η corresponds to a lower failure rate and a higher reliability. The deterioration curve is then generated by subsisting increased values of x, the age of the elevator and computing the corresponding condition reliability as shown in Fig. 2.

The deterioration behavior depicted in Fig. 2 shows a highly reliable system during the early years. This curve shows that an elevator can be still in a good condition even after 20 years if properly maintained. However, after that point, the performance starts to dramatically deteriorate with time towards the end of its service life. Typically, elevators can last for 25-30 years if they are properly maintained.

V. Conclusion

Estimating the deterioration of systems and their underlying components of healthcare facilities is an integral step in the maintenance management of such complex assets. It was concluded from the analysis of the previous studies that most of them capitalized on using some deterioration patterns which may not be compatible with the available datasets. As such, a holistic comparison of some of the widely acknowledged stochastic distributions is carried out. In this paper, one vital system, the conveying system, is selected to be studied. The deterioration of the selected system was modelled stochastically leveraging historical condition data. Various distribution probabilities were fitted and the model with the highest performance was selected based on different statistical testing metrics. The parameters of the selected distribution were then found utilizing maximum likelihood estimate and the deterioration curves were established. The developed methodology in this study is expected to support decision makers in better planning for their maintenance and rehabilitation programs as well as drafting more efficient and realistic budgeting policies.

References

[1] Abdallah, M., & El-Rayes, K. 2016. Multiobjective optimization model for maximizing sustainability of existing buildings. Journal of Management in Engineering, 32(4), 04016003.

[2] *Ahmed, R., & Zayed, T. 2019.* Criticality Assessment of Hospital Building Systems. Canadian Society for Civil Engineering Annual Conference, Laval QC, Canada.

[3] Azzalini, A., & Valle, A. D. 1996. The multivariate skew-normal distribution. Biometrika, 83(4), 715-726.

[4] Balakrishnan, N., & Chen, W. S. 1999. Handbook of tables for order statistics from lognormal distributions with applications. Springer Science & Business Media.

[5] Bortolini, R., & Forcada, N. 2019. A probabilistic performance evaluation for buildings and constructed assets. Building Research & Information, 1-18.

[6] Edirisinghe, R., Setunge, S., & Zhang, G. 2015. Markov model—based building deterioration prediction and ISO factor analysis for building management. Journal of Management in Engineering, 31(6), 04015009.

[7] Farahani, A., Wallbaum, H., & Dalenbäck, J. O. 2019. Optimized maintenance and renovation scheduling in multifamily buildings–a systematic approach based on condition state and life cycle cost of building components. Construction management and economics, 37(3), 139-155.

[8] Grussing, M. N., Liu, L. Y., Uzarski, D. R., El-Rayes, K., & El-Gohary, N. 2016. Discrete Markov approach for building component condition, reliability, and service-life prediction modeling. Journal of Performance of Constructed Facilities, 30(5), 04016015.

[9] Grussing, M. N., Uzarski, D. R., & Marrano, L. R. 2006. Condition and reliability prediction models using the Weibull probability distribution. In Applications of Advanced Technology in Transportation (pp. 19-24).

[10] *Hovde, P. & Moser, K. 2004.* Performance based methods for service life prediction. International Council for Research and Innovation in Building and Construction, CIB, Rotterdam.

[11] ISO 2016. ISO15686-3, Part 3: Performance audits and reviews. ISO Standard, 121124.

[12] Jardine, A. K., & Tsang, A. H. 2013. Maintenance, replacement, and reliability: theory and applications. CRC press.

[13] Kirkham, R. J., & Boussabaine, A. H. 2005. Forecasting the residual service life of NHS hospital buildings: a stochastic approach. Construction Management and Economics, 23(5), 521-529.

[14] Kotz, S., & Nadarajah, S. 2000. Extreme value distributions: theory and applications. World Scientific.

[15] Kumar, D., Setunge, S., & Patnaikuni, I. 2010. Prediction of life-cycle expenditure for different categories of council buildings. Journal of performance of constructed facilities, 24(6), 556-561.

[16] Lavy, S., & Shohet, I. M. 2007. On the effect of service life conditions on the maintenance costs of healthcare facilities. Construction management and economics, 25(10), 1087-1098.

[17] *Lounis, Z. 2000.* Reliability-Based Life Prediction of Aging Concrete Bridge. In PRO 16: International RILEM Workshop on Life Prediction and Aging Management of Concrete Structures (Vol. 16, p. 229). Rilem Publications.

[18] Madanat, S., Mishalani, R., & Ibrahim, W. H. W. 1995. Estimation of infrastructure transition probabilities from condition rating data. Journal of infrastructure systems, 1(2), 120-125.

[19] Marshall, A. W., & Olkin, I. 2014. Multivariate Exponential Distributions, Marshall–Olkin. Wiley StatsRef: Statistics Reference Online.

[20] Marteinsson, B. 2003. Durability and the factor method of ISO 15686-1. Building research & information, 31(6), 416-426.

[21] Morcous, G. 2006. Performance prediction of bridge deck systems using Markov chains. Journal of performance of Constructed Facilities, 20(2), 146-155.

[22] Salah, M., Osman, H., & Hosny, O. 2018. Performance-based reliability-centered maintenance planning for hospital facilities. Journal of Performance of Constructed Facilities, 32(1), 04017113.

[23] Shohet, I. M., Puterman, M., & Gilboa, E. 2002. Deterioration patterns of building cladding components for maintenance management. Construction Management & Economics, 20(4), 305-314.

[24] van Noortwijk, J. M. 2009. A survey of the application of gamma processes in maintenance. Reliability Engineering & System Safety, 94(1), 2-21.

[25] Rigby, R.A. and Stasinopoulos, D.M., 2006. Using the Box-Cox t distribution in GAMLSS to model skewness and kurtosis. Statistical Modelling, 6(3), pp.209-229.

[26] Stacy, E.W., 1962. A generalization of the gamma distribution. The Annals of mathematical statistics, 33(3), pp.1187-1192.

[27] Swain, J.J., Venkatraman, S. and Wilson, J.R., 1988. Least-squares estimation of distribution functions in Johnson's translation system. Journal of Statistical Computation and Simulation, 29(4), pp.271-297.